# Distributed Big Data Analytics
# Efficient First Order Inductive Learner on Spark

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**Definition 7**. A tuple satisfies a learning rule if it satisfies one of the Horn clauses of this rule.
For every relation a set of the $\oplus$tuples which belong to this relation is given. For a target relation a set of $\oplus$tuples is also given. A set of the $\ominus$tuples not belonging to the target relation may be given. The statement is introduced: if some tuple is not included in set $\oplus$tuples then it is $\ominus$tuple.

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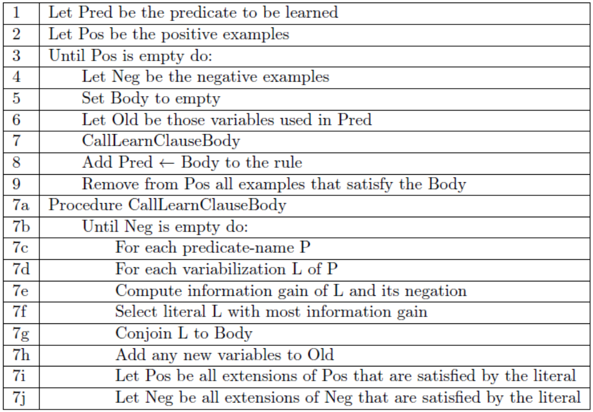
**Problem statement:** Using Spark framework realize FOIL to find a learning rule as a set of Horn clauses for the target relation that consistent with given positive examples and not cover any given negative examples.

## Approach

Foil algorithm is realized using Scala in Spark framework.



| | |
|---|---|
| 1 | Let Pred be the predicate to be learned |
| 2 | Let Pos be the positive examples |
| 3 | Until Pos is empty do: |
| 4 | Let Neg be the negative examples |
| 5 | Set Body to empty |
| 6 | Let Old be those variables used in Pred |
| 7 | CallLearnClauseBody |
| 8 | Add Pred $\leftarrow$ Body to the rule |
| 9 | Remove from Pos all examples that satisfy the Body |
| 7a | Procedure CallLearnClauseBody |
| 7b | Until Neg is empty do: |
| 7c | For each predicate-name P |
| 7d | For each variabilization L of P |
| 7e | Compute information gain of L and its negation |
| 7f | Select literal L with most information gain |
| 7g | Conjoin L to Body |
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| 7i | Let Pos be all extensions of Pos that are satisfied by the literal |
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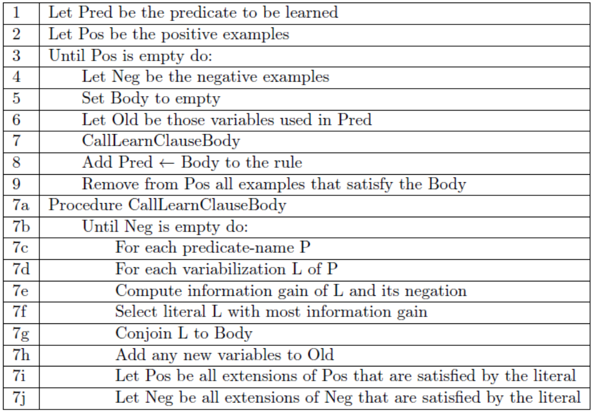

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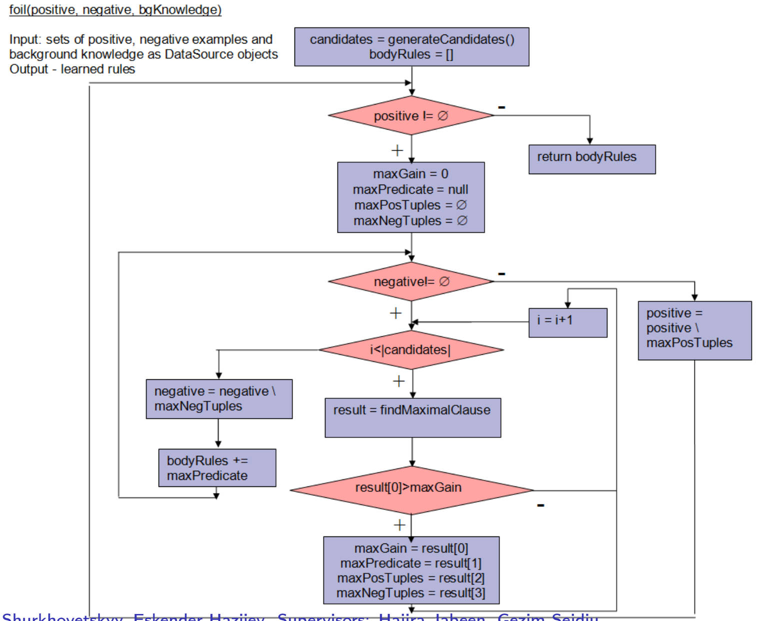
To select literal with greatest positive gain:

$$gain(L_i) = n_i^{\oplus\oplus} \cdot (I(T_i) - I(T_{i+1})), \quad I(T_i) = -\log_2(n_i^{\oplus}/(n_i^{\oplus} + n_i^{\ominus})), \qquad (2)$$

$n_i^{\oplus}$ — a number of $\oplus$tuples in $T_i$, $n_i^{\ominus}$ — a number of $\ominus$tuples in $T_i$,
$n_i^{\oplus\oplus}$ — a number of the $\oplus$tuples in $T_i$ represented by one or more tuples in $T_{i+1}$.

# Implementation


foil(positive, negative, bgKnowledge)
Input: sets of positive, negative examples and background knowledge as DataSource objects
Output - learned rules
candidates = generateCandidates()
bodyRules = []
positive != ∅
-
return bodyRules
+
maxGain = 0
maxPredicate = null
maxPosTuples = ∅
maxNegTuples = ∅
negative!= ∅
-
positive = positive \ maxPosTuples
+
i = i+1
i<|candidates|
negative = negative \ maxNegTuples
bodyRules += maxPredicate
+
result = findMaximalClause
result[0]>maxGain
-
+
maxGain = result[0]
maxPredicate = result[1]
maxPosTuples = result[2]
maxNegTuples = result[3]

## Evaluation

Evaluation metrics: $\rho_k(A_1, A_2) = |n_k(A_1) - n_k(A_2)|,\ k = 1, 2, 3.$

Indicators: $n_1(A) = \frac{n^{\oplus}_{\text{covered}}(A)}{n^{\oplus}_{\text{given}}}$, $n_2(A) = \frac{n^{\ominus}_{\text{covered}}(A)}{n^{\ominus}_{\text{given}}}$, $n_3(A) = \mathrm{runtime}(A)$.

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Experiment 1. (a), results: $daughter(X_1, X_2) \leftarrow female(X_1) parent(X_2, X_1)$; covered $\oplus$ examples: (Emily, Tom), (Mary, Ann); covered $\ominus$ examples: $\emptyset$.

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Experiment 2. (b), results: $daughter(X_1, X_2) \leftarrow female(X_1)parent(X_2, X_1)$; covered $\oplus$ examples: (Opra, Ann), (Kate, Ann), (Lina, Kate), (Gail, Hovard); covered $\ominus$ examples: $\emptyset$.

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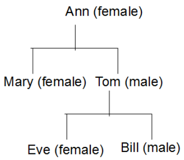
Experiment 3. (b), results: $son(X_1, X_2) \leftarrow male(X_1)parent(X_2, X_1)$; covered $\oplus$ examples: (Ryan, Uve), (Bill, Opra), (Hovard, Ann), (Nick, Kate), (Uve, Ann), (Tom, Uve); covered $\ominus$ examples: $\emptyset$.



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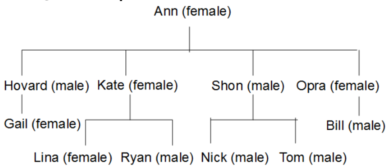

(b)

Table 2. Efficiency indicators.

| No Experiment | Proportion of covered $\oplus$(%) examples | Proportion of covered $\ominus$ examples (%) | Running time (sec) |
|---|---|---|---|
| 1 | 100 | 0 | 0.188 |
| 2 | 100 | 0 | 0.207 |
| 3 | 100 | 0 | 0.200 |

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3. Testing FOIL with scoring function different from original *InformationGain* function (i.e. *Leverage* function, *LaplaceAccuracy*, etc).

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2. Gaining experience in project testing and selection of evaluation datasets.
3. Getting deeper understanding of how and when to apply distributed means of data processing.

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